DETECTION AND REMOVAL OF LINE SCRATCHES IN DEGRADED MOTION PICTURE SEQUENCES.

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ABSTRACT

Line scratches are a common problem in archived motion pictures. They are caused by the abrasion of the film material as it passes through the projection mechanism. This paper presents a technique for detecting and removing these line artefacts. The method employs a model of the line profile for detection and the 2D Autoregressive model (2D AR) of the image for interpolation.

1 INTRODUCTION

Line scratches are a prominent artefact in archived motion picture films. Film post production houses, e.g. Quantel, Kodak, Disney, expend some effort in manual correction of these defects. They manifest as lines of bright or dark intensity, oriented more or less vertically over much of the image. They may be caused when material from some particle is smeared vertically over the film material in the projector or by the abrasion of the film as it passes over some particle caught in the mechanism. A typical example is shown in figure 1. This problem is quite different from the missing data problem which has been addressed in [1]. Unlike Dirt and Sparkle[1] a line scratch persists in the same spatial location for more than one frame. It cannot be characterized as a temporal discontinuity.

In order to address the problem of detection, therefore, the paper begins with a consideration of the features of a line artefact. This is important since line features can occur as a natural part of an image, but the contrast, thickness and vertical extent of the line can be used to define its quality as a defect in the image. Section 3 then outlines a process for generating line candidates which are then evaluated according to a probabilistic criterion set out in Section 4. Line interpolation is then achieved through a stochastic non-stationary 2D AR interpolator implemented using overlapped data windows. This paper concentrates more on the detection of the line artefacts.

[1] Patches of constant intensity distributed randomly throughout the sequence in space and time.

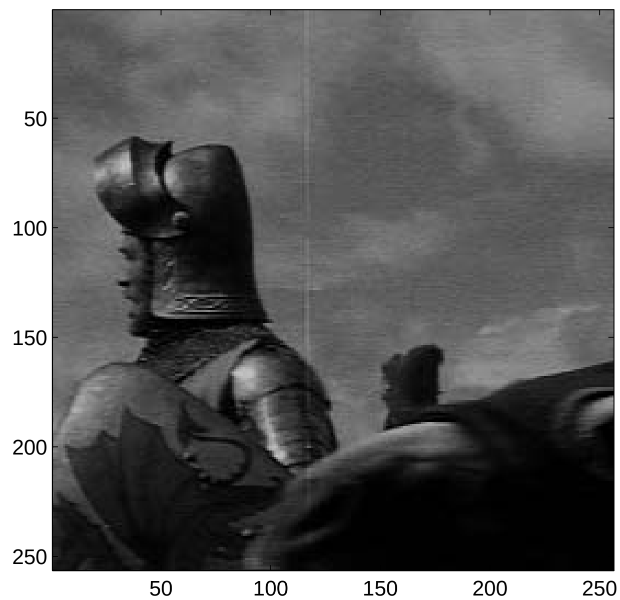

Figure 1: Degraded Original Frame of KNIGHT.

2 LINE FEATURES AND A MODEL FOR DEGRADATION

A horizontal cross-section through the line artefact illustrated in figure 1 is shown in figure 2. This section was generated by taking the vertical mean of the columns after correcting for a space varying local mean image intensity. The shape of the section is similar to a damped sinusoid and illustrates a characteristic of line defects as opposed to other horizontally impulsive features : *the line scratch is accompanied by sidelobes of appreciable intensity.*[2] To further limit the class of lines treated, it is assumed that the line exists over the entire vertical length of the frame, and that it is not curved.

The line profile may therefore be modelled by a damped sinusoid as below (where i, j are the horizontal and vertical abscissa)

$$L_n^{(p)}(i,j) = b_p k_p^{|i-(m_p j + c_p)|} \cos\left(\frac{3\pi |i-(m_p j+c_p)|}{2w_p}\right) \quad (1)$$

[2] Dark fringes accompany lines of high intensity and vice versa.

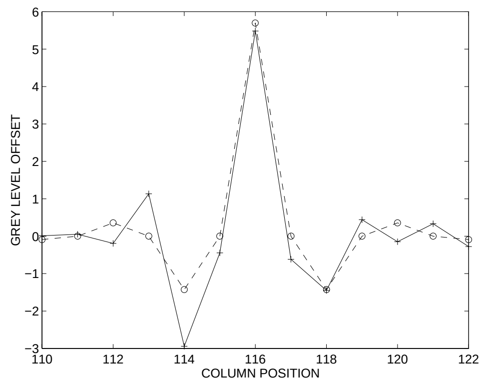

Figure 2: Cross section of the line at column 116 in figure 1 (solid) and of a matched line profile using equation 1 (dashed, $w = 3.0, k = 0.5, b = 5.5$).

where $\vec{x} = [i, j]$, m_p, c_p are the slope and intercept with the horizontal edge of the image which defines the orientation of the pth straight line profile $L_n^{(p)}(i, j)$, w_p is defined as the line width, b_p is the brightness of the central portion of the line and k_p is the decay of the line profile such that $0.05 < k_p < 0.95$.

Denoting the intensity of the degraded image at position $\vec{x}$ as $G(\vec{x})$ and the original, clean image as $I(\vec{x})$, the distortion caused by P lines (whose maximum magnitude occur at horizontal positions $\vec{x}_p = [x_p,\ 0])$) is assumed to be

$$G(\vec{x}) = I(\vec{x}) + \sum_{p=0}^{P-1} L_n^{(p)}(\vec{x} - \vec{x}_p) + e(\vec{x}) \qquad (2)$$

where $e(\vec{x})$ is additive Gaussian noise $\sim \mathcal{N}(0, \sigma_e^2)$.

Because P is not known beforehand, detection of lines using this model is complicated, in fact it is a type of model order selection problem. Morris [2] employs a *Reversible Jump* [3] technique which proposes lines for verification (as well as rejects proposals) as part of a Monte Carlo scheme for line detection. However it is possible to take a much less compute intensive, but successful route. This paper proposes to make a pessimistic estimate of the number and location of lines by using a simpler, deterministic process. This is then followed by a Bayesian refinement strategy which rejects or accepts proposals from the deterministic stage.

3 DETERMINISTIC PRE-PROCESSING

The distorted image (figure 1) is *vertically subsampled* by a factor s, after low pass filtering using a vertically oriented Gaussian filter, yielding an image denoted $G_s(i, j)$. This procedure enhances vertical line features and suppresses noise. Line features which are artefacts are vertically smooth but horizontally impulsive. These features may be detected in the subsampled image, $G_s(i, j)$, by thresholding the signal $e(i, j) = G_s(i, j) - M_s(i, j)$. Where $M_s(i, j)$ is the horizontally

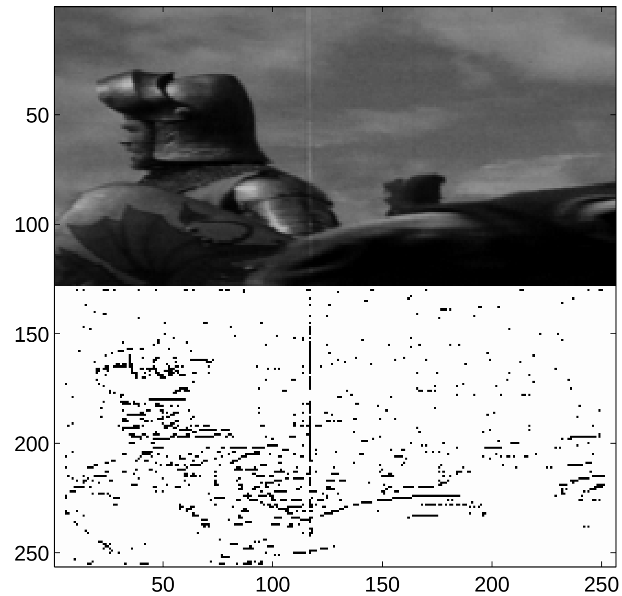

Figure 3: **Top**: Low passed and subsampled version of figure 1; **Bottom**: Thresholded median error (threshold = 3)

median filtered $G_s(i, j)$. $e(i, j)$ will be large at sites of horizontal impulses; it is vertically correlated at line scratch sites. This is because the median filter will remove lines with a width that is roughly less than its window. Thus the Hough Transform[3] of the binary field resulting from thresholding yields candidate lines. The choice of median filter and threshold level is made less important because the purpose of this stage is to point out candidate line features.

In practice it is sufficient to employ a 5 tap horizontal median filter and a threshold of 3 grey levels for an 8 bit grey scale image. Note that the threshold is positive for bright lines and negative for dark lines. This method of impulse detection was employed by Paisan et al. for 1-D signals [4]. It is convenient to place an extremely conservative threshold on the height of the peaks selected in the Hough space, (H_t say) to avoid selecting peaks corresponding to lines which are certainly spurious. This is made possible because the height of the Hough bins is proportional to the number of pixels flagged as being part of a particular line. Given the assumption that line artefacts traverse a substantial portion of the image frame, then it is reasonable to select Hough bins which have some substantial line contribution. An additional feature which may be incorporated in this stage is the number of lines which are required to be removed. Thus each peak is visited in turn from the maximum to the minimum, the first N lines say, which exceed the bin threshold are selected for removal.

The subsampled image in figure 1 ($s = 2$) is shown in

[3]The transform is performed over a small range of slope, not only vertical.

figure 3 along with the binary threshold output (value of 3 grey levels). In this case only bright lines were considered. Generally, It is found sufficient to calculate the bins of the Hough transform between the ranges $m_p = -0.1 : .01 : 0.1$ and $c_p = 0 : 0.5 : N_1$ for an image with N_1 columns (using Matlab notation). These values were used in processing the bottom of figure 3, in addition $N = 2$ and $H_t = 40$. Two lines were then selected at $[m, c] = [0, 116]; [0, 56]$.

4 BAYESIAN REFINEMENT

Having employed the Hough Transform to find likely line candidates it is now necessary to evaluate them as line artefacts and choose those most likely to fit the line profile model defined in equation 1. Proceeding in a Bayesian fashion and denoting the parameter vector as $\mathbf{P} = [k_p, b_p, w_p, m_p, c_p, \sigma_e^2]$, the probability of the parameters for the pth line given the data may be written

$$p(\mathbf{P}|G(\vec{x}), I(\vec{x})) \propto p(G(\vec{x})|\mathbf{P}, I(\vec{x}))p(\mathbf{P}, I(\vec{x})) \tag{3}$$

The likelihood can be written as a Normal distribution of errors, $(\mathbf{E} = [e(\vec{x}_1), e(\vec{x}_2), \ldots])$

$$p(G_n(\vec{x})|\mathbf{P}, I_n(\vec{x})) \propto \exp\left(-\frac{1}{\sigma_e^2}\sum_{\vec{x}\in\mathcal{P}}[G(\vec{x}) - L^{(p)}(\vec{x}) - I(\vec{x})]^2\right) \tag{4}$$

where $\mathcal{P}$ is an area which includes the pth line. These expressions may be solved to locate the MAP or ML solution for the parameter vector for each line. However, rather than take this approach, it is found to be useful to numerically investigate the marginal distribution for the brightness, $p(b_p)$. Examination of this distribution will then indicate the importance of the line. The line feature is assumed to be significant if $p(b_p \leq 1.0) < Rp(b_p > 1.0)$. In other words, when a significant proportion (measured by R) of the marginal probability distribution for the brightness is concentrated below the grey level 1.0; the line indicated is a false alarm. The use of the grey level 1.0 as a fixed point is due purely to considerations of perceptual visibility.

4.1 Gibbs sampling

Each line candidate provides an initial estimate of m_p, c_p. These values are kept fixed as it is found in practice that the peaks of the Hough Transform correspond well with the line centres if a true line is found. Making the assumption that $M(i,j)$ is a good estimate of $I(i,j)$ for detection, Gibbs sampling [2, 5] can then be employed[4] to provide marginal probability densities for the remaining parameters, $b_p, w_p, k_p, \sigma_e^2$.

Gibbs sampling is a well known stochastic technique. In this case, it is executed by successively drawing samples from the conditional distributions $k_p \sim p(k_p|\mathbf{P}, I(\vec{x}))$, $w_p \sim p(b_p|\mathbf{P}, I(\vec{x}))$, $b_p \sim p(b_p|\mathbf{P}, I(\vec{x}))$, given the current values of the other parameters at each random draw. After some *burn in* period, the sequence of samples drawn converge to samples from the marginal distributions $p(k_p)$, $p(w_p)$, $p(b_p)$, $p(\sigma_e^2)$ respectively. It is possible to determine exactly the expressions for the conditional distributions for b_p, σ_e^2 since the required integrations are standard. The distributions are as follows

$$p(b_p|\mathbf{P}, I(\vec{x})) = \mathcal{N}(L_2/L_1, \sigma_e^2/L_1) \tag{5}$$

$$p(\sigma_e|\mathbf{P}, I(i,j)) \propto \sigma^{-N}\exp\left(-\frac{|\mathbf{E}|^2}{2\sigma_e^2}\right) \tag{6}$$

where
$$L_1 = \sum_{\vec{x}\in\mathcal{P}} L_p(\vec{x})^2$$
$$L_2 = \sum_{\vec{x}\in\mathcal{P}}[G(\vec{x}) - I(\vec{x})]L_p(\vec{x})$$

and $|\mathbf{E}|^2$ is the sum squared error in equation 4. Hence drawing samples for b_p, w_p is simple (See [5]). However sampling for k_p, w_p is difficult. In order to avoid the computational cost of Metropolis-Hastings sampling, the allowed ranges for each of these parameters is quantized to $0.05 : 0.05 : 0.95$ and $0.5 : 0.5 : 5.0$ respectively, assuming a maximum w_p of 5 pixels. Then the conditional probability distribution over each of these ranges can be calculated numerically using equation 3. This can then be normalized and a sample for the quantized variable drawn using the Cumulative p.d.f. It is found that the sequences of samples converges very quickly to the marginal distributions, typically within the first 10 iterations.

Figure 4 shows two histograms of the two lines which were selected as candidates from the output of the deterministic process on Figure 1. The line at $c = 56$ is a false alarm and can be seen to be differentiated from the line at $c = 116$ (which is the true line) by the fact that its distribution is mostly concentrated below $b = 1.0$. Note that in the actual implementation it is assumed that $I(i,j)$ can be well approximated by $M(i,j)$, where $M(i,j)$ is a horizontally median filtered version of $G(i,j)$ at the full original scale.

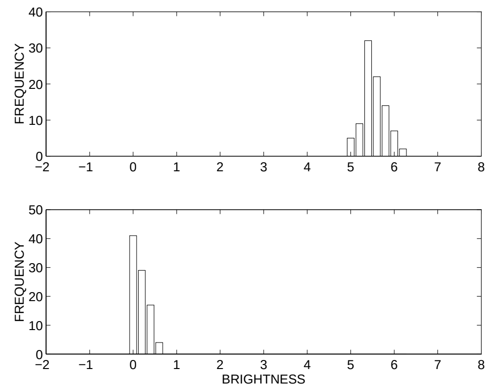

Figure 4: Histograms of the 1st 100 samples of b (after 10 sample *burn in*. **Top**: True line, c = 116; **Bottom**: False alarm, c = 56.

[4]With uniform priors, suitable parameter ranges, and a Chi Squared prior on σ_e^2.

5 INTERPOLATION

Equation 2 is not good enough for line removal[5]. Therefore, the conservative assumption is made that the line scratch has obliterated data in the region of the artefact. The basis of the interpolation scheme is the assumption that the image data is generated from a 2D Autoregressive system. As such the AR prediction equations in the region of the line artefact can be defined as follows

$$\mathbf{e} = \mathbf{A}\mathbf{g} \tag{7}$$

where $\mathbf{e}$ represents a vector of excitation values drawn from $\mathcal{N}(0, \sigma_e^2)$, $\mathbf{g}$ is a vector of image values containing both known and unknown image pixel sites at and around the region of the line artefact. Rather than estimate the missing values of $\mathbf{g}$ using Least Squares[6] (LS) [1] a probabilistic approach is taken which avoids problems of the excitation tending to zero in large missing regions. This idea was presented in [6] for missing data reconstruction in image sequences. It generates interpolants by sampling the posterior probability density for the unknown data given the assumption that the excitation is drawn from a Normal distribution. This sampled process is preferred here instead of the LS solution because any blurring caused by that solution is more obvious in the case of this visually striking vertical image feature. The reader is encouraged to refer to [6] for further details. The AR parameters are estimated using weighted least squares in the region of the line artefact. To allow for varying image statistics it is possible to incorporate space varying AR parameters directly into the equation 7. However, it is sufficient to perform the interpolation piecemeal in regions of overlapped blocks along the line, and then to use a data window to combine the blocks. This method was used with a Hanning window, and 16×16 blocks with $2:1$ overlap to create the restoration shown in figure 5. The width of the line is chosen as the MAP estimate numerically evaluated from the samples generated in the line verification stage. For figure 5, $w = 3.0$.

6 FINAL COMMENTS

The symbiosis of deterministic and stochastic methods in the solution of image processing problems is a rich area of study. This paper has presented just such a hybrid technique for line detection and removal. The overall concept is that a deterministic pre-processing algorithm can yield a very good starting point for a stochastic process, allowing the power of MCMC methods (for example) to be used in a practical (low cost) solution by improving the convergence of the stochastic optimization stage. In this particular paper, the *Bayesian* reader may recognize that the verification of the line candidates is perhaps better done by employing model evidence [5] rather than the use of a *soft decision threshold* on one of the parameters. This

[5]e.g. the profile changes vertically.

[6]and so minimizing $|\mathbf{e}|^2$

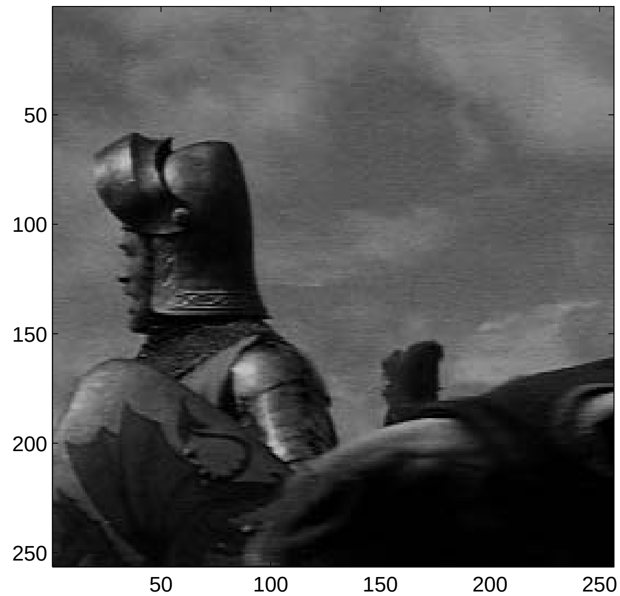

Figure 5: Reconstruction of bright line artefact at $c = 116$ in figure 1, ($w = 3$), using 2D AR interpolation.

is to be investigated in future work. Also of interest is the possibility of incorporating the AR image model for $I(i, j)$ directly into the line detection stage. This will lead to a unified Bayesian strategy for line detection and removal.

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